Sprint Assessment Using Machine Learning And A Wearable Accelerometer

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Abstract

Field-based sprint performance assessments rely on metrics derived from a simple model of sprinting dynamics parameterized by 2 constants, v0 and τ, which indicate a sprinter's maximal theoretical velocity and the time it takes to approach v0, respectively. This study aims to automate sprint assessment by estimating v0 and τ using machine learning and accelerometer data. To this end, photocells recorded 10-m split times of 28 subjects for three 40-m sprints while wearing an accelerometer around the waist. Features extracted from the accelerometer data were used to train a classifier to identify the sprint start and regression models to estimate the sprint model parameters. Estimates of v0, τ, and 30-m sprint time (t30) were compared between the proposed method and a photocell method using root mean square error and Bland–Altman analysis. The root mean square error of the sprint start estimate was .22 seconds and ranged from .52 to .93 m/s for v0, .14 to .17 seconds for τ, and .23 to .34 seconds for t30. Model-derived sprint performance metrics from most regression models were significantly ($P < .01$) correlated with t30. Comparison of the proposed method and a physics-based method suggests pursuit of a combined approach because their strengths appear to complement each other.

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Sprint Assessment Using Machine Learning and a Wearable Accelerometer

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Field-based sprint performance assessments rely on metrics derived from a simple model of sprinting dynamics parameterized by 2 constants, v_0 and τ, which indicate a sprinter's maximal theoretical velocity and the time it takes to approach v_0, respectively. This study aims to automate sprint assessment by estimating v_0 and τ using machine learning and accelerometer data. To this end, photocells recorded 10-m split times of 28 subjects for three 40-m sprints while wearing an accelerometer around the waist. Features extracted from the accelerometer data were used to train a classifier to identify the sprint start and regression models to estimate the sprint model parameters. Estimates of v_0, τ, and 30-m sprint time (t_{30}) were compared between the proposed method and a photocell method using root mean square error and Bland–Altman analysis. The root mean square error of the sprint start estimate was .22 seconds and ranged from .52 to .93 m/s for v_0, .14 to .17 seconds for τ, and .23 to .34 seconds for t_{30}. Model-derived sprint performance metrics from most regression models were significantly ($P < .01$) correlated with t_{30}. Comparison of the proposed method and a physics-based method suggests pursuit of a combined approach because their strengths appear to complement each other.

Keywords: wearable sensor, inertial sensor, sprint assessment, statistical learning

Recent developments in field-based sprint assessments[1–5] enable athlete-specific force–velocity profiling allowing targeted training.[6,7] These employ a simple model describing a sprinter's velocity (v) over time (t) as per the following equation[8]:

$$\frac{dv}{dt} = a_m - \frac{v}{\tau}. \tag{1}$$

The model assumes a positive acceleration originating with muscular contraction (a_m) and a damping force (v/τ) due to muscle's force–velocity property.[8] The solution to Equation 1 expresses the sprinter's velocity, $v(t)$, and position, $p(t)$, as functions of time (t) as per the following equation[1,8]:

$$v(t) = v_0(1 - e^{-t/\tau}), \tag{2}$$

$$p(t) = v_0(t + \tau e^{-t/\tau}) - v_0\tau. \tag{3}$$

In Equations 2 and 3, the product $a_m \times \tau$ was originally used instead of v_0, but in recent papers, v_0 is used because it is understood to be the horizontal asymptote of Equation 2. Physically, v_0 represents the theoretical velocity of the sprinter should they sprint indefinitely and never fatigue, while τ is related to the time it takes to approach v_0 (specifically, $\dot{v}(0) = v_0/\tau$). The physical interpretation of these parameters makes their utility as performance metrics clear—increases in v_0 or the ratio v_0/τ are associated with improved sprint performance.

In practice, these constants are estimated for an athlete using position–time or velocity–time data and Equation 3 or 2, respectively.[1–5,7] Experiments have been conducted for smartphone camera,[4] photocell,[1] and global positioning system (GPS)-determined[5] position–time data along with radar[1] and magnetic-inertial measurement unit[2,3] (MIMU)–determined velocity–time data. MIMU methods are attractive because they can provide additional metrics to augment the force–velocity-based sprint assessment including step-average 3-dimensional ground reaction force,[9] instantaneous sprint velocity,[3,10] trunk lean angles,[11] and spatiotemporal parameters.[12,13] MIMU-based estimates of sprint velocity are subject to integration drift and thus require compensatory methods. Setuain et al[2] incorporated photocell-based estimates of velocity to perform this compensation, but this removes some of the advantages of a MIMU-only system. We recently explored incorporating Equation 2 for drift compensation[3] and found that underestimates of τ may have contributed more than v_0 to velocity estimation error.

The MIMU methods discussed here are limited by sensor imperfections and model assumptions. In other biomechanics contexts, some employ machine learning (ML) techniques both for classification[14–17] and regression.[18–24] Mannini and Sabatini[18] estimated running speeds less than 3 m/s, and it is unknown how a similar approach might perform for sprinting. Thus, in this study, we investigated the concurrent validity of estimating v_0 and τ using an automated ML approach and wearable accelerometer data. An accelerometer-only method was pursued because removing the requirement of the gyroscope significantly extends battery life.

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Methods

Subjects

In total, 28 subjects (12 females and 16 males; age: 20.9 [2.3] y, height: 1.73 [0.09] m, and body mass: 71.1 [11.7] kg) participated in this study. Subjects were either collegiate-level sprinters (n = 16) or untrained (n = 12), reported no musculoskeletal injuries for the previous 6 months, were physically active, and were able to perform maximal-effort sprints pain free. All subjects provided written consent to participate. The Appalachian State University Institutional Review Board approved this study.

Experimental Protocol

Subjects performed a general and sprint-specific warm-up concluding with sprint starts from a 4-point stance to familiarize themselves with the sprint test protocol. Each subject performed 3 maximal-effort 40-m sprints with a MIMU (450 Hz, 28 g, accelerometer range: ±24 g, and gyroscope range: ±2000°/s; Yost's 3-Space Sensor Data Logger; YEI Technology, Portsmouth, OH) attached to an elastic strap provided by the manufacturer strapped around the subject's waist with the sensor placed over the sacrum. For each sprint trial, data were recorded during the subject's approach to the start line, transitioning to a 4-point stance and maintaining for a 3-second countdown, the sprint and ensuing deceleration, and walking back to the start line. Photocells (Brower Timing Systems, Draper, UT) recorded position–time data and were initiated once the subject's hand was lifted off a touch sensor. A high-speed video camera (200 frames per second; Sensor Technologies America, Carrollton, TX) was used to time synchronize the photocell and sensor-determined sprint starts.[1,3] This synchronization method[3] identifies the time difference in the video frames corresponding to the defined sprint start of each instrument (thumb off pressure sensor for photocell and initial forward movement of the MIMU).

Photocell-Based Sprint Assessment

The constants v_0 and τ were determined for each subject for each sprint by fitting the position–time data at each 10-m split to Equation 3[1,4] and served as the truth data to train and validate the regression models. Since regression models are improved with more observations and the photocells failed to register the 40-m time for some of the sprints, only the 10-, 20-, and 30-m split times were used in this study. Of the 84 sprint trials, the photocell system false triggered for 4 (4 different subjects). Furthermore, the distribution of both constants was checked for outliers (values more than 2 times the interquartile range above the sample's 75th percentile) of which 2 from different subjects were identified. These 6 trials (2 outliers and 4 false triggers) were removed, leaving a total of 78 sprint trials available for analysis.

Accelerometer-Based Sprint Assessment

The proposed ML method consists of 2 steps: (1) estimation of the sprint start instant and (2) estimation of v_0 and τ. We used a support vector machine classifier (radial basis kernel) to estimate the sprint start and 4 regression models for estimating v_0 and τ: lasso, ridge, elastic net, and support vector regression (radial basis kernel). Each data set is divided into 5-second, 100% overlapping windows (consecutive windows differed by 1 sample), and each window is divided into 2 subwindows: the first 1.5 seconds and the last 3.5 seconds from which features are extracted. These features are used to classify the sample 1.5 seconds into the window as either a "sprint start" or "not a sprint start." Features[21] include mean, variance, range, kurtosis, maximum signal spectral power, and the associated frequency from the x, y, z, and resultant acceleration. These were obtained from 2 signal bandwidths: low-pass filtered at 70 Hz and band-pass filtered at 0.25 and 70 Hz. We also identified the frequency below which 90% of signal power is contained for the unfiltered x, y, z, and resultant acceleration yielding 104 total features extracted from each window of data.

Model Training and Validation

To test the ML approach and reduce overfitting, we reserved trials from 5 randomly selected subjects (ie, 15 trials) for model testing (referred to as TEST) and used the remaining 63 trials for training (referred to as TRAIN). To remove irrelevant data (before stance and after deceleration), we programmatically truncate each data set such that the last sample is at the maximum resultant acceleration (always occurred during deceleration) and the first sample is that occurring 12 seconds prior to this instant. An estimate of the true sprint start obtained from the MIMU[3] along with the 104 features describing the associated sprint start window was used to train the classifier. Regression models for v_0 and τ were trained using features describing the 3.5 seconds after the sprint start from TRAIN along with sex as an additional categorical feature (1 for females and 0 for males) for a total of 53 features. Lasso, ridge, and elastic net regressions determine linear models between the features vector ($\boldsymbol{x}$) and each response. Since the linearity of v_0 or τ with respect to any one feature x_i varies, we determined the linear relationship between each response vector ($\boldsymbol{y}_r$), where r denotes the response (v_0 or τ), and the jth element of $\boldsymbol{y}_r$ corresponds to the jth observation in TRAIN ($j \in \mathbb{N}$, $1 \le j \le 63$), and each of the 53 features (x_i, $i \in \mathbb{N}$, $1 \le i \le 53$) in $\boldsymbol{x}$ for 5 different transforms (f_k, $k \in \{-1, 0, 1, 2, 3\}$) along with the associated residual sum of squares (RSS_k),

$$\text{RSS}_k = (\boldsymbol{y}_r - H_k(H_k^T H_k)^{-1} H_k^T \boldsymbol{y}_r)^T (\boldsymbol{y}_r - H_k(H_k^T H_k)^{-1} H_k^T \boldsymbol{y}_r), \quad (4)$$

where

$$H_k = \begin{pmatrix} f_k(x_{i,1}) & 1 \\ \vdots & \vdots \\ f_k(x_{i,63}) & 1 \end{pmatrix}, \quad (5)$$

and

$$f_k(x_{i,j}) = \begin{cases} x_{i,j}^k & \text{for } k = -1,1,2,3 \\ \ln(x_{i,j}) & \text{for } k = 0 \end{cases}. \quad (6)$$

The transform that minimized RSS for each feature was used for linearization (note that no transform is included for $k = 1$). The classifier and regression models were trained using TRAIN data, and optimal hyperparameters were determined via 10-fold cross-validation. Model training was performed in R Studio 3.4.3 using the e1071 package[25] to train the support vector machine and support vector regression models and the glmnet package[26] to train the lasso, ridge, and elastic net regression models.

To test the proposed ML method, we first obtained an estimate of the sprint start in each TEST trial using the classifier trained using TRAIN. Our estimated sprint start is determined using the window that is statistically most likely to be a sprint start (ie, the window with the highest posterior probability). Next, the features from the latter 3.5 seconds of this window along with sex and each feature's optimal transform are used to estimate v_0 and τ using each of the 4 regression models. We estimated 30-m sprint time by numerically solving Equation 3 for $p(t_{30}) = 30$ m. Root mean square error (RMSE),

Table 1 Comparison of the Reference Photocell Estimates of v_0, τ, and 30-m Sprint Time (t_{30}) to the Estimates Made by the Different Regression Techniques

	Photocell	Lasso	Ridge	Elastic net	SVR
v_0, $\bar{v}_0$ (SD)	8.76 (0.97)	8.43 (0.97)	8.25 (0.67)	8.41 (0.96)	8.21 (0.38)
RMSE	–	.52	.64	.52	.93
Bias, %	–	–2.97	–5.75	–4.17	–6.02
LOA, %	–	–14.40 to 6.45	–14.25 to 2.74	–14.42 to 6.07	–23.24 to 11.21
τ, $\bar{\tau}$ (SD)	1.03 (0.14)	0.98 (0.07)	0.97 (0.04)	0.98 (0.07)	0.94 (0.02)
RMSE	–	.14	.15	.14	.17
Bias, %	–	–4.18	–4.88	–4.10	–7.85
LOA, %	–	–30.64 to 22.23	–34.82 to 25.06	–31.56 to 23.35	–38.29 to 22.60
t_{30}, $\bar{t}_{30}$ (SD)	4.48 (0.38)	4.58 (0.43)	4.62 (0.33)	4.58 (0.43)	4.60 (0.17)
RMSE	–	.25	.23	.25	.34
Bias, %	–	2.13	3.29	2.29	2.90
LOA, %	–	–7.25 to 11.51	–4.14 to 10.72	–6.93 to 11.52	–11.51 to 17.32

Abbreviations: LOA, limits of agreement; RMSE, root mean square error; SVR, support vector regression. Note: v_0 in unit meters per second, τ and t_{30} in unit seconds, and bias and LOA expressed as a percentage of the mean.

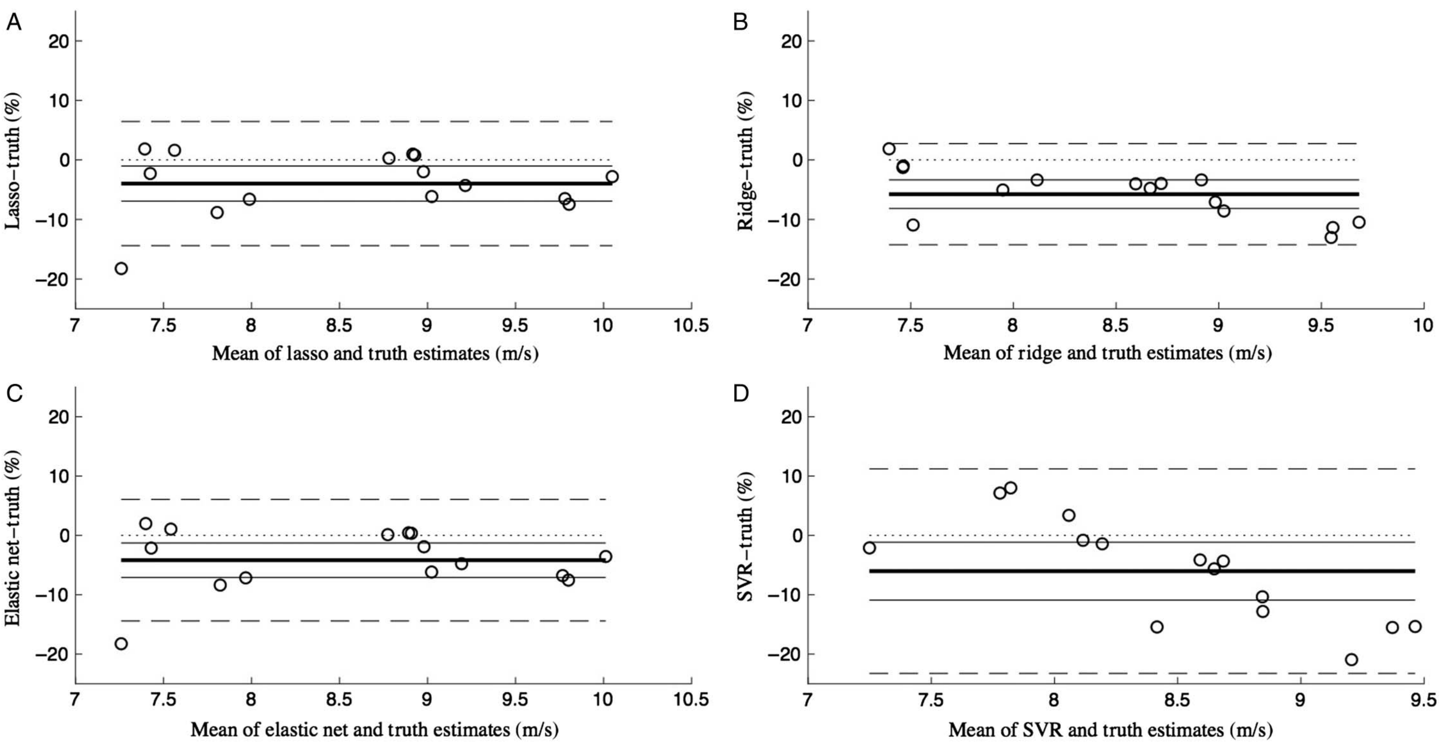

Figure 1 — Bland–Altman plots comparing estimates of v_0 from the photocell method and the proposed ML method: (A) lasso, (B) ridge, (C) elastic net, and (D) SVR. The percent differences between methods are plotted against the mean of the estimates for each sprint trial in TEST. In each figure, the solid line is the bias, the dashed lines are the 95% limits of agreement, and the dotted line is the line of equality (0). ML indicates machine learning; SVR, support vector regression; TEST, group of datasets removed from model training for validation.

percent bias, and Bland–Altman 95% limits of agreement were used to assess the performance of the classifier and regression models. Absolute bias was considered first, but percent bias was chosen in an attempt to compensate for an apparent relationship between magnitude and measurement error.[27] The ability of the predicted sprint constants to discriminate performance was assessed using the Pearson product-moment correlation between the true t_{30} and both v_0 and v_0/τ (note $v_0/\tau = a_m$ in Equation 1).

Results

The RMSE of the predicted sprint start instant was .22 seconds with a bias of –0.08 seconds, and the limits of agreement ranged from –0.50 to 0.35 seconds. The performance of the regression models is detailed in Table 1, and Bland–Altman plots are provided in Figures 1–3. Across all regression techniques, RMSE ranged from .52 to .93 m/s for v_0 (–2.97% to 6.02% bias), .14 to .17 seconds

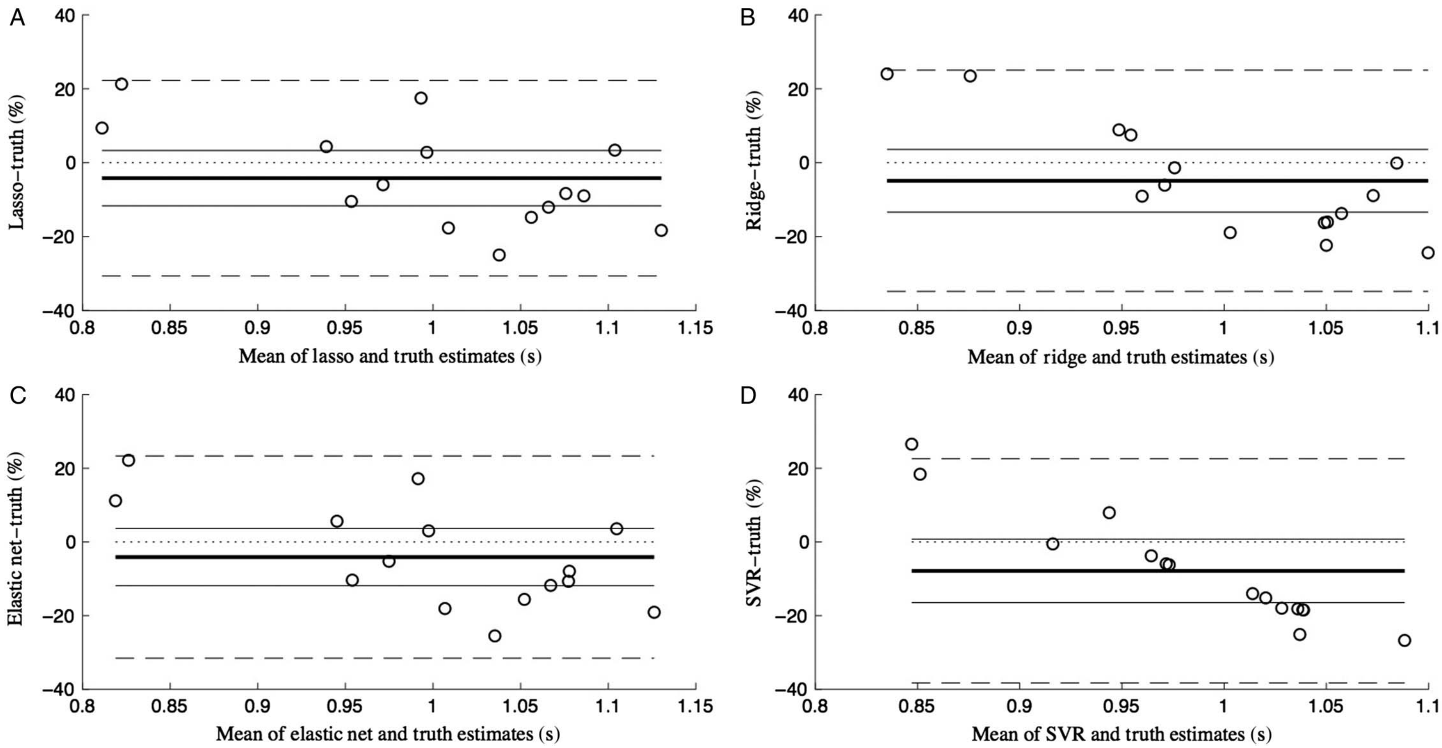

Figure 2 — Bland–Altman plots comparing estimates of τ from the photocell method and the proposed ML method: (A) lasso, (B) ridge, (C) elastic net, and (D) SVR. The estimate differences between methods are plotted against the mean of the estimates for each sprint trial in TEST. In each figure, the solid line is the bias, the dashed lines are the 95% limits of agreement, and the dotted line is the line of equality (0). ML indicates machine learning; SVR, support vector regression; TEST, model testing.

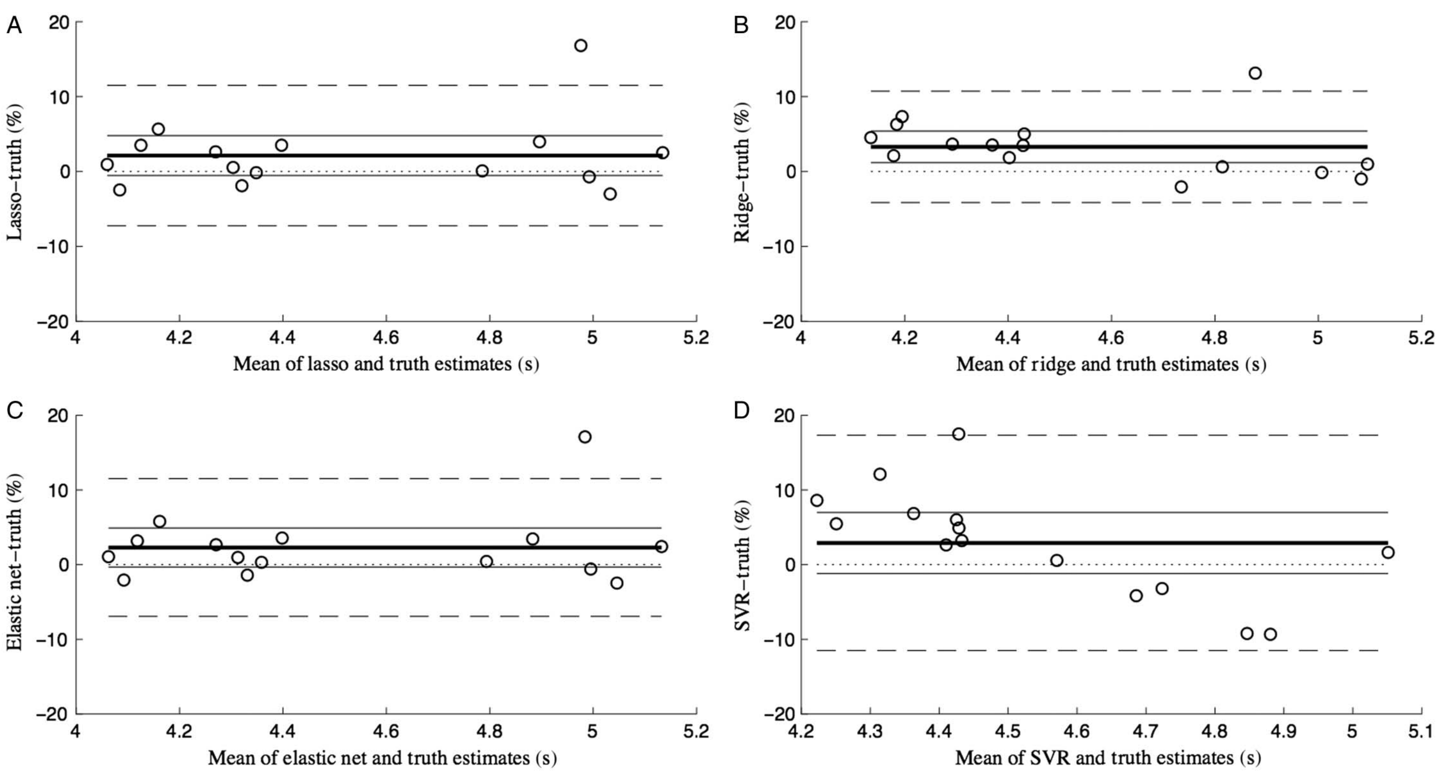

Figure 3 — Bland–Altman plots comparing estimates of t_{30} determined by the sprint models from the photocell method and the proposed ML method: (A) lasso, (B) ridge, (C) elastic net, and (D) SVR. The estimate differences between methods are plotted against the mean of the estimates for each sprint trial in TEST. In each figure, the solid line is the bias, the dashed lines are the 95% limits of agreement, and the dotted line is the line of equality (0). ML indicates machine learning; SVR, support vector regression; TEST, model testing.

for τ (−7.85% to −4.10% bias), and .23 to .34 seconds for t_{30} (2.13% to 3.29% bias). The narrowest and widest limits of agreement were found via ridge regression (−14.25% to 2.74%) and support vector regression (−23.24% to 11.21%), respectively, for v_0, via lasso regression (−30.64% to 22.23%) and support vector regression (−38.29% to 22.60%), respectively, for τ, and via ridge regression (−4.14% to 10.72%) and support vector regression (−11.51% to 17.32%), respectively, for t_{30}. Significant relationships were determined between t_{30} and estimates of v_0 from the lasso ($r = -.82$, $P < .01$), ridge ($r = -.89$, $P < .01$), elastic net ($r = -.83$, $P < .01$), and support vector regression ($r = -.54$, $P < .05$) models. Relationships between t_{30} and v_0/τ were significant for lasso ($r = -.88$, $P < .01$), ridge ($r = -.89$, $P < .01$), and elastic net ($r = -.89$, $P < .01$) models, but not for support vector regression ($r = -.38$, $P = .16$).

Discussion

This paper presents an automated sprint assessment method using accelerometer data. Automation was primarily due to the support vector machine estimate of the sprint start and is unlike other MIMU-based techniques, which require visual inspection of the data.[2,3] The .22-second RMSE of the sprint start may be too large to automate a physics-based MIMU approach since the error linearly propagates to t_{30} estimation error.[3,10] Nonetheless, the ridge regression informed a model capable of estimating t_{30} within .23-second RMSE. The proposed method appears capable of discriminating performance given the strong relationships between performance metrics with t_{30} (save the support vector regression estimate of v_0/τ). Compared with a physics-based MIMU method,[3] the proposed method showed larger error in estimating v_0 (bias less than −2.97% vs 0.01%), but was better for τ (bias between −4.10% and −7.85% vs 11.0%).

The proposed ML sprint assessment method is practically attractive because it is automated and the required equipment is low-cost and consumes minimal battery power. The estimation error of v_0 was larger than that reported for a physics-based MIMU method, but estimates of τ appear to be superior. Thus, future research should investigate combined ML and physics-based techniques because their estimation strengths may complement each other. The reported error statistics for the proposed method are only expected within the described intended use: The sprint is in a straight line of no more than 30 m, the sprinter is nonfatigued,[8] and accelerometer data begin recording just before the sprint start stance and end after the deceleration phase.

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The authors declare that they have no conflict of interest.

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